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The Social Distribution of Health: Estimating Quality-Adjusted Life Expectancy in England

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ABSTRACT

Objective: To model the social distribution of quality-adjusted life expectancy (QALE) in England by combining survey data on health-related quality of life with administrative data on mortality. **Methods:** Health Survey for England data sets for 2010, 2011, and 2012 were pooled (n = 35,062) and used to model health-related quality of life as a function of sex, age, and socioeconomic status (SES). Office for National Statistics mortality rates were used to construct life tables for age-sex-SES groups. These quality-of-life and length-of-life estimates were then combined to predict QALE as a function of these characteristics. Missing data were imputed, and Monte-Carlo simulation was used to estimate standard errors. Sensitivity analysis was conducted to explore alternative regression models and measures of SES. **Results:** Socioeconomic inequality in QALE at birth was estimated at 11.87 quality-adjusted life-years (QALYs), with a sex difference of 1 QALY. When the socioeconomic-sex subgroups are ranked by QALE, a differential of 10.97 QALYs is found between the most and least healthy quintile groups. This differential can be broken down into a life expectancy difference of 7.28 years and a quality-of-life adjustment of 3.69 years. **Conclusions:** The methods proposed in this article refine simple binary quality-adjustment measures such as the widely used disability-free life expectancy, providing a more accurate picture of overall health inequality in society than has hitherto been available. The predictions also lend themselves well to the task of evaluating the health inequality impact of interventions in the context of cost-effectiveness analysis.

Keywords: health inequalities, health surveys, population health, quality-adjusted life-years.

Introduction

There are various ways of summarizing a population's overall lifetime experience of health by combining information on both mortality and morbidity. Perhaps the best known metrics are disability-free life expectancy (DFLE) and healthy life expectancy (HLE), which subtract years from life expectancy (LE) using a binary indicator of ill-health or disability. Recent efforts have been made to incorporate more sophisticated measures of morbidity into health expectancy estimates. Studies by Mathers et al. [1] and Salomon et al. [2] combined injury and disability prevalence rates with a set of disability weights to estimate disability- or health-adjusted LE, thereby reflecting the severity of conditions, not just their presence. Quality-adjusted life expectancy (QALE) is another recent approach to estimating health expectancy that uses a continuous ratio scale variable to measure morbidity, thus enabling it to incorporate detailed multiattribute data on health-related quality of life (HRQOL). The rising popularity of the quality-adjusted life-year (QALY) metric through its use in health technology assessment has led to its inclusion in national health surveys, affording researchers the opportunity to estimate QALY weights for a wide range of population subgroups using large, nationally representative data sets. Implementation of the QALE metric in health inequality research, however, has been limited to regional analyses [3], despite widespread application of other health expectancy indicators to inequality measurement [4,5].

As well as health inequality measurement, estimating the social distribution of QALE can potentially play a role in addressing policy trade-offs between improving total population health and reducing unfair health inequality [6,7]. This form of "equity-efficiency trade-off" can sometimes occur, for example, if a policy intervention is cost-effective but increases health inequality or if a policy intervention reduces health inequality but is not cost-effective. Although health inequality reduction objectives are prominent in the rhetoric of public health bodies [8], routine economic evaluation of health care and public health interventions considers only cost-effectiveness. The baseline social distribution of health that is estimated in this study can potentially be used to model the distributional impacts of future interventions in distributional cost-effectiveness analysis [9], which allows equity and efficiency to be traded-off explicitly in the modeling process.

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The aim of this study is to generate predictions of QALE for age, sex, and socioeconomic groups using nationally representative survey data and mortality rates. By combining these with the associated population estimates, we then create a rank ordering of the population by QALE that reflects social inequalities in health. The merits of this endeavor are twofold. First, a QALE distribution will allow for the effects of health care and public health interventions to be modeled directly on population health using methods and metrics consistent with cost-effectiveness analysis. Second, using the QALY in population health measurement provides a more sensitive indicator of morbidity as compared with DFLE and HLE.

Methods

Our analysis has four distinct stages. First, using data in the Health Survey for England (HSE), we predict HRQOL weights as a function of age, sex, and socioeconomic status (SES), with the latter measured by the index of multiple deprivation (IMD), a small area deprivation indicator. Second, predictions of life expectancy are generated from national mortality data for age-sex-SES groups using life tables. Both stages are then combined to create a multivariate prediction of QALE for age-sex-SES groups. Last, population estimates for each group are used to create the social distribution of health.

Data and Variables

The analysis uses pooled data from the three most recent rounds of the HSE in 2010, 2011, and 2012, with a combined sample size of 35,062. The HSE is an annual series that monitors a range of health conditions and risk factors for the noninstitutionalized population. It uses a multistage stratified probability sampling design with a sampling frame of Postcode Address File that tries to ensure that every member of the population has an equal chance of being selected, details of which are covered in Boniface et al. [10].

Health status is measured using the EuroQol five-dimensional questionnaire (EQ-5D) [11], a generic instrument used in health technology assessment around the world to assess the treatment effects of interventions for a wide range of different health conditions [12,13]. The EQ-5D is a questionnaire that asks respondents to rate their own health in five dimensions: pain, mobility, anxiety/depression, self-care, and usual activities. In the original three-level EQ-5D version used in this study, subjects rate their health on each dimension using one of three possible levels: no problems, some problems, or severe problems. This generates a possible 245 health states when including the two additional states "unconscious" and "dead" ($3 \times 3 \times 3 \times 3 \times 3 + 2$). A single index figure is then given to each health state on the basis of a country-specific tariff. The standard UK value set estimated by Dolan et al. [14] was applied to our data. This analysis is restricted to adults aged 16 years and older, leaving a sample size of 25,320. This is because the EQ-5D is not responsive to the HRQOL for children younger than this age for whom there are other more appropriate instruments [15].

The SES variable used was the most recently available IMD from 2010. This is a weighted area deprivation index of 38 variables covering seven dimensions of deprivation (employment, income, education, health, crime, living environment, and housing/services) that is given to each of the 32,482 lower layer super output areas in England. In 2010, the median layer super output area population was 1551 with an interquartile range of 1429 to 1708 and 99% had fewer than 2731 residents. More information on the methods used to construct the IMD can be found in McLennan et al. [16]. The raw IMD score is not reported in the HSE; thus, the variable used in the regression analysis is the population IMD quintile group, with the first quintile group representing the most deprived and those in the fifth having the lowest deprivation. The mortality data are reported for IMD decile groups; thus, we apply the same HRQOL scores to both decile groups contained in a quintile group (i.e., quintile group 1 to decile groups 1 and 2) during the QALE prediction process outlined below.

We focus on age, sex, and SES as covariates because these are often of interest in public health campaigns and are associated with large inequalities in population health. An additional advantage of using this set of variables is that they are readily available in the data used in cost-effectiveness studies, allowing for the easy estimation of subgroup-specific costs and effects. Data on age and sex are routinely collected in any study or survey, while IMD can be ascertained from an individual's postcode.

Regression Analysis

The distribution of EQ-5D utility score is heavily skewed: the proportion of individuals reporting severe problems on any of the dimensions is rare, ranging from 0.18% for mobility to 4.29% for pain, whereas the number reporting perfect health is more than half, at 52.72%. In addition, the utility data have an upper ceiling of 1. Although these properties suggest that a linear regression model may not be appropriate, we use ordinary least squares (OLS) as our estimator for two principal reasons. First, previous studies have shown OLS to perform well in comparison with other types of estimators when used to model HRQOL, particularly when using large sample sizes such as those in the HSE [17–19]. Second, the principal diagnostic instrument for judging accurate HRQOL prediction is accurate mean EQ-5D scores for age-sex-SES groups because it is these that are used to adjust the life tables in the QALE process described below. This means that any potential imprecision of individual predicted scores caused by applying a linear model is not a cause for concern. Using OLS also has an additional benefit, in that the estimated coefficients can be directly interpreted and used to predict the EQ-5D scores (and therefore the QALE) for different populations than the one used in this study. We also perform sensitivity analysis using alternative two-part and Tobit models, as described below.

All statistical analyses are performed in Stata 12. Standard survey data analysis tools are used to incorporate the probability weights supplied in the data and to account for the fact that scores within households, the primary sampling unit, can be correlated (which may distort statistical inference by reducing the standard errors).

Another issue was missing HRQOL data, with significant item nonresponse occurring within the sample. A total of 3177 (12.6%) observations were missing a utility score, with these individuals, on average, tending to be older, male, nonwhite, and living in more deprived areas than the complete cases. A logit model regressing the probability of "missingness" on our variables of interest was used to determine whether the data are missing completely at random—that missingness is not systematic or related to individual characteristics [20]. This found that age, race, and sex (though not deprivation level) are statistically significant predictors ($P < 0.01$), correctly predicting 88% of the cases with missing values. This justified the use of predictive mean matching to impute missing values, given the non-normal distribution of utility scores. Following the recommendations of White et al. [21], the number of imputations is set at 5, while the number of values from which the EQ-5D is drawn in the predictive mean matching process is set at 3. Following imputation, predicted EQ-5D scores are generated by regressing individual utility values on age, sex, and SES group. From these we

calculate group means for the age-sex-SES groups, weighting each year within a group by its within-group sample density (because age structure is not uniform within a 5-year band). Alternative models are run to determine the model specification, one with age-SES and age-sex interaction terms and a second with a quadratic age term to test for nonlinearity with respect to utility.

Life Tables

National data on populations and deaths for 5-year age bands by sex and IMD decile group are obtained from the Office for National Statistics for 2011, from which we calculate crude mortality rates for each group. These are used to construct 20 abridged life tables using the Chiang II method [22] to obtain estimates of LE for each of the 360 age-sex-SES groups (2 sexes, 10 IMD groups, 18 age intervals). We assume that that any individual dying during an age interval is assumed to have survived half the length of the interval. Expected LE at the start of an age interval is estimated by dividing the number of years lived in that and all successive intervals by the number of people alive at the beginning of the interval:

$$e_{xds} = \frac{\sum_x^z L_{xds}}{I_{xds}}$$

where e_{xds} is LE at the start of age interval x for deprivation decile group d and sex s; z is the last age interval; L_{xds} is the total number of years lived by the surviving cohort in interval x; and L_{xds} is the surviving cohort at the start of the interval.

LE is then adjusted for HRQOL using the predicted utility scores for each age-sex-SES group, via the Sullivan method [23]. Because we were unable to estimate HRQOL for people aged 0 to 15 years, we assume that they experience the same average HRQOL as do those in the youngest age group for which the HRQOL could be estimated (16–19 years). Obtaining the QALE estimate is nearly the same as for LE, except that we multiply the years lived in each age interval by the associated QALY weight, $\overline{u}_{xds}$:

$$\text{QALE}_{xds} = \frac{\sum_x^z (L_{xds} * \overline{u}_{xds})}{I_{xds}}$$

Additional life tables are constructed for further analyses: by IMD quintile group for each sex to enable comparisons with previous health expectancy studies and by IMD quintile group combining sexes to enable a non–gender-specific SES inequality estimate.

QALE

We analyze inequalities in QALE in three ways. Socioeconomic and sex inequalities are estimated separately from the supplementary life tables just described. We then construct an overall univariate distribution of health that reflects both types of disparities. This is done by first assuming that the prediction of QALE at birth is the same for all individuals within a sex-SES group (regardless of their age). We can then multiply each of the 20 sex-SES group QALE predictions by the number of people in the group, taken from Office for National Statistics population estimates, and rank the whole population from lowest to highest QALE. The additional benefit of this distribution is that we account for the relative sizes of the sex-SES groups as well as the magnitude of the inequalities between them. A Monte-Carlo simulation is performed to account for uncertainty over the two sets of parameters in the model, mortality rates and utility scores. A total of 1000 simulations are performed, from which standard errors and 95% confidence intervals are constructed for QALE at birth for both sexes. Subgroup distributions can also be estimated by reconfiguring the base year, from at birth to any point at life, depending on the population of interest. We reestimate the distribution at 25, 40, and 65 years to demonstrate this.

Sensitivity Analysis

Two alternative types of estimators are adopted to check the robustness of the OLS findings. These more complex model specifications allow for the skewed and bounded nature of the outcome variable. A two-part model (2PM) is adept at handling data in cases in which a high proportion of observations is at one end of the distribution, whereas the Tobit model [24] was specifically intended for analyzing censored data, and has been previously advocated for handling HRQOL data [25].

Judgment on the suitability of the estimators is based on several diagnostic measures. Mean-squared error and mean absolute error (MAE) are computed for each estimator, with MAE also reported for the mean group scores and for the 360 QALE predictions. Although these might not be conclusive as to which estimator is the most appropriate, they should give some indication as to how well they model EQ-5D and QALE for the purposes of this study. We performed these estimations on the complete case data. This enables us to compare their relative performance with OLS without the additional complications of using the imputed data set, particularly for the 2PM.

As a further sensitivity analysis, we alter the SES variable used in the regression analysis to the National Statistics Socioeconomic Classification (NS-SEC) category, which classifies individuals into eight groups on the basis of their occupation [26]. This is to validate the legitimacy of using IMD as our SES variable and to provide potentially useful information for researchers working with data sets that contain only the NS-SEC category and not IMD. Because the age-specific mortality data are by IMD decile and quintile groups and not the NS-SEC group, it is necessary to create a mapping between the two so that mean EQ-5D scores by the latter (8 categories) could be applied to life tables partitioned by the former (5 and 10 categories).

Results

Descriptive Statistics

Descriptive statistics for a number of relevant subgroups are presented in Table 1. Disease prevalence was strongly correlated with age, sex, and SES, supporting our variable selection. These associations were adequately captured by the EQ-5D, which declined with age, while women of all ages reported lower mean utility at all stages of life. Utility decreased in a roughly linear fashion as deprivation increased, from 0.79 in the least deprived quintile group to 0.88 in the most deprived.

EQ-5D Prediction

Regression results using imputed data sets are reported in Table 2. Compared with complete case regressions, there was a smaller constant and smaller effect sizes for all covariates. Prediction performance against the observed scores was worse, with a marginally higher MAE for individual and group mean utility scores. Interactions between age, sex, and SES were rejected. All other covariates were statistically significant ($P < 0.01$). The signs on all coefficients were consistent with the descriptive relationships: lower deprivation was associated with higher HRQOL, while ageing and being female were associated with lower HRQOL. The quadratic age term was also negative, indicating larger HRQOL decrements for each additional year. Mean group scores ranged from 0.98 (16–19-year-old males in the IMD quintile group 5) to 0.68 (85+ females in quintile group 1). The prediction accuracy of OLS, shown in Figure A1 in Supplemental Materials found at

Table 1 – Sample statistics with average EQ-5D scores.

Variable	N	% Sample	Utility	Variable	N	% Sample	Utility
Total	35,062	–	0.842	IMD quintile group			
Age (y)				1 (most deprived)	6,665	19	0.793
0–15	9,742	28	–	2	6,763	19	0.826
16–24	2,555	7	0.928	3	6,935	20	0.839
25–34	3,642	10	0.915	4	7,060	20	0.860
35–44	4,340	12	0.877	5 (least deprived)	7,639	22	0.880
45–54	4,423	13	0.844	NS-SEC			
55–64	4,077	12	0.799	I	2,886	8	0.905
65–74	3,434	10	0.795	II	5,556	16	0.871
75+	2,849	8	0.723	III	3,580	10	0.847
Sex				IV	2,160	6	0.839
Male	16,204	46	0.856	V	1,791	5	0.814
Female	18,858	54	0.832	VI	4,440	13	0.810
Race				VII	3,270	9	0.784
White	30,617	87	0.870	VIII	484	1	0.792
Nonwhite	4,334	12	0.840	Not available	10,895	31	–
Not available	111	0	–				

Notes.

1. Percentages are rounded and may not exactly sum to 100.
2. Those aged 0 to 15 y were assumed to have utility equal to that of those aged 16 to 19 y.
3. The index of multiple deprivation (IMD) is an area-level indicator of deprivation. The National Statistics Socioeconomic Classification (NS-SEC) is an occupation-based indicator of socioeconomic status.

EQ-5D, EuroQol five-dimensional questionnaire.

Table 2 – Results from regressing the EQ-5D score on age, sex, and socioeconomic status (measured by the index of multiple deprivation [IMD]).

Variable	OLS (imputed) EQ-5D score	OLS (complete) EQ-5D score	Tobit model	2PM EQ-5D score
IMD quintile group				
1 (most deprived)	Reference	Reference	Reference	Reference
2	0.0341* (0.00650)	0.0372* (0.00598)	0.0652* (0.0117)	0.0425* (0.00874)
3	0.0475* (0.00631)	0.0512* (0.00585)	0.0881* (0.0116)	0.0629* (0.00855)
4	0.0747* (0.00579)	0.0802* (0.00549)	0.148* (0.0112)	0.0954* (0.00806)
5 (least deprived)	0.0857* (0.00563)	0.0937* (0.00539)	0.175* (0.0114)	0.108* (0.00782)
Age	−0.00219* (0.000472)	−0.00200* (0.000416)	−0.00751* (0.000962)	−0.00477* (0.000654)
Age^2	$-7.98 \times 10^{-6\dagger}$ (4.79×10^{-6})	$-1.55 \times 10^{-5*}$ (4.29×10^{-6})	2.87×10^{-7} (8.91×10^{-6})	$2.28 \times 10^{-5*}$ (6.24×10^{-6})
Sex				
Male	Reference	Reference	Reference	Reference
Female	−0.0210* (0.00324)	−0.0253* (0.00286)	−0.0590* (0.00629)	−0.0148* (0.00466)
Constant	0.935* (0.0115)	0.943* (0.00947)	1.327* (0.0252)	0.798* (0.0164)
Observations	25,320	22,143	22,143	10,469
MAE	0.156	0.155	0.155	0.135
Group MAE	0.0273	0.0245	0.0212	0.0213
QALE MAE	0.541	0.399	0.351	0.434

Notes. Standard errors are in parentheses.

1. N = 35,062; 25,320 were 16 y or older; 22,143 had complete EQ-5D responses; 10,469 had an EQ-5D score not equal to 1 for the two-part model (2PM) regression.
2. Mean absolute error (MAE) is the distance between predicted and observed EQ-5D scores. The prediction error of mean scores for the age-sex-IMD groups gives us the group MAE. Quality-adjusted life expectancy (QALE) MAE is the prediction error, measured in quality-adjusted life-years, of the 360 QALE estimates against those made when using observed EQ-5D scores.
3. Output for 2PM is from the second stage, whereas MAE relates to both parts of the model.

EQ-5D, EuroQol five-dimensional questionnaire; OLS, ordinary least squares.

* $P < 0.01$.

† $P < 0.1$.

Table 3 – Comparisons of absolute and relative inequality in quality-adjusted and unadjusted life expectancy by index of multiple deprivation (IMD) quintile group and sex.

IMD quintile group	Male	Female	Combined
	Life expectancy		
1 (most deprived)	75.2 (0.061)	79.9 (0.060)	77.5 (0.044)
2	78.0 (0.061)	81.9 (0.056)	80.0 (0.041)
3	79.8 (0.058)	83.3 (0.054)	81.6 (0.040)
4	81.3 (0.056)	84.3 (0.052)	82.8 (0.038)
5 (least deprived)	82.6 (0.058)	85.4 (0.055)	84.0 (0.040)
Mean	79.4	83.0	81.2
Absolute IMD gap	7.4 (0.084)	5.5 (0.082)	6.5 (0.060)
Relative IMD gap	0.10 (0.001)	0.07 (0.001)	0.08 (0.001)
Absolute sex gap	3.60		
Relative sex gap	0.05		
	Quality-adjusted life expectancy		
1 (most deprived)	62.3 (0.348)	64.1 (0.375)	63.2 (0.343)
2	67.0 (0.327)	68.2 (0.330)	67.7 (0.306)
3	69.5 (0.309)	70.4 (0.317)	70.0 (0.289)
4	72.8 (0.264)	73.4 (0.267)	73.2 (0.236)
5 (least deprived)	74.8 (0.183)	75.2 (0.181)	75.1 (0.134)
Absolute IMD gap	12.5 (0.323)	11.2 (0.339)	11.9 (0.328)
Relative IMD gap	0.20 (0.006)	0.17 (0.006)	0.19 (0.006)
Absolute sex gap	0.74		
Relative sex gap	0.01		

Notes. Absolute gap is Q5 − Q1. Relative gap is (Q5/Q1) − 1. Standard errors are given in parentheses.

http://dx.doi.org/10.1016/j.jval.2015.03.1784, is higher for lower deprivation groups in which the relationship between age and HRQOL is more linear. The full distribution of EQ-5D scores is available from the authors on request.

QALE

Adjusting LE for HRQOL had substantial impacts on inequality, shown in Table 3. The direction of this impact depends on which dimension of inequality we focus on. Adjusting for HRQOL increased the absolute difference between the least and the most deprived quintile groups from 6.5 years to 11.9 QALYs. Conversely, sex inequality was reduced, reflecting higher female morbidity. Inequality at birth between sexes dropped from 3.6 years to 1.0 QALYs. The standard errors generated from the simulation, also reported in Table 3, averaged 0.29 QALYs across IMD and sex groups, resulting in 95% confidence intervals of around 1.2 QALYs. The full range of QALE predictions is detailed in Table 4.

The univariate distribution of LE and QALE at birth, which reflects both types of inequality and the relative group sizes, is displayed in Figure 1 and Table A1 in Supplemental Materials found at http://dx.doi.org/10.1016/j.jval.2015.03.1784. The disparity between the top and bottom quintile groups increases when adjusting for morbidity, from 7.3 years to 11.0 QALYs. The healthiest experience the equivalent of 88% of their LE in full health, whereas this figure drops to 82% for the least healthy. The population distributions at 25, 40, and 60 years (see Table A2 in Supplemental Materials found at http://dx.doi.org/10.1016/j.jval.2015.03.1784) show that relative inequality between the least and the most healthy increases with age, from 0.17 at birth to 0.32 at 65 years.

Sensitivity Analysis

Comparative model diagnostics, along with the regression output, are reported in Table 2 and Figure A1. OLS, Tobit, and 2PM estimation all yield comparable results, with none substantially outperforming the others. Mean absolute deviations in QALE prediction from those using observed scores were all less than 0.5 QALYs.

QALE predictions do not markedly change when the NS-SEC replaces IMD quintile groups as the SES variable in the HRQOL regression (results available from the authors on request). All the coefficients except age squared were statistically significant ($P < 0.01$). The average difference in predicted QALE across population quintile groups between mapped and nonmapped estimates is 0.7 QALYs. One statistic that was noticeably different was absolute inequality between the least and the most healthy population quintile groups, which increased from 11.0 to 14.0 QALYs.

Discussion

Principal Findings

This study has demonstrated that adjustment for morbidity using detailed patient-reported data on HRQOL substantially increased the size of socioeconomic health inequality when compared with LE alone. Figure 2, using additional numbers from the Office for National Statistics [27], compares estimates of LE, QALE, and DFLE at birth for males in the least and the most deprived quintile groups. A male in quintile group 1 is expected to experience 83 years, 75 QALYs, or 70 disability-free life-years. The discrepancies between these figures clearly demonstrate the impact of using the QALY, rather than a binary disability indicator, to measure morbidity. The increased sensitivity of the former to states of illness and disability creates a more realistic picture of health experience and a more accurate measure of health inequalities. Our absolute inequality estimate of 11.9 QALYs between the least and the most deprived quintile groups (Table 3) is consistent with Collins' [3] figure of 12.7 QALYs from a regional analysis of QALE disparities.

Causal inference was not required or attained in the regression framework used in this study because we aimed only to describe how expected lifetime health varies by age, sex, and SES. Therefore, concerns about residual confounding, model fit, and other diagnostic measures are relevant only if the estimates are

Table 4 – Predicted quality-adjusted life expectancy by 5-y age group, sex, and index of multiple deprivation (IMD) quintile group (1 = most deprived).

Age (y)	Male						Female					
	IMD 1	IMD 2	IMD 3	IMD 4	IMD 5	Mean	IMD 1	IMD 2	IMD 3	IMD 4	IMD 5	Mean
0–4	62.3	67.0	69.5	72.8	74.8	69.3	64.1	68.2	70.4	73.4	75.2	70.5
5–9	58.3	62.7	65.1	68.2	70.2	64.9	60.1	64.0	66.1	68.9	70.7	66.2
10–14	53.8	58.1	60.4	63.4	65.3	60.3	55.7	59.5	61.5	64.2	65.9	61.6
15–19	49.4	53.5	55.7	58.6	60.4	55.6	51.4	55.0	56.9	59.5	61.1	57.0
20–24	45.0	49.0	51.1	53.9	55.6	50.9	47.1	50.5	52.3	54.8	56.4	52.5
25–29	40.7	44.5	46.6	49.2	50.8	46.4	42.8	46.1	47.9	50.2	51.7	48.0
30–34	36.5	40.1	42.1	44.6	46.1	42.0	38.6	41.7	43.4	45.6	47.1	43.6
35–39	32.4	35.8	37.7	40.0	41.5	37.6	34.5	37.4	39.1	41.1	42.5	39.3
40–44	28.5	31.6	33.4	35.6	37.0	33.4	30.6	33.3	34.8	36.7	38.1	35.1
45–49	24.7	27.6	29.3	31.2	32.6	29.3	26.8	29.2	30.7	32.5	33.7	31.0
50–54	21.2	23.7	25.2	27.0	28.3	25.3	23.1	25.4	26.7	28.3	29.5	27.0
55–59	17.8	20.0	21.4	23.0	24.1	21.5	19.6	21.6	22.9	24.3	25.4	23.1
60–64	14.6	16.5	17.7	19.2	20.2	17.9	16.4	18.1	19.2	20.5	21.5	19.5
65–69	11.8	13.4	14.4	15.6	16.5	14.5	13.3	14.8	15.8	16.8	17.7	16.0
70–74	9.3	10.5	11.3	12.2	13.0	11.5	10.6	11.7	12.5	13.4	14.2	12.8
75–79	7.1	8.0	8.6	9.3	9.9	8.8	8.2	9.0	9.6	10.2	10.9	9.9
80–84	5.3	5.9	6.2	6.8	7.3	6.5	6.1	6.6	7.0	7.4	8.0	7.3
85+	3.9	4.3	4.4	4.8	5.2	4.7	4.4	4.7	4.9	5.2	5.6	5.3

Note. The predictions apply to the first year of each group.

used to evaluate an intervention that could potentially alter the deprivation level or the SES. Nevertheless, the selected covariates do exhibit strong associations with utility scores, justifying the measurement of inequality with respect to them.

Results were robust to a wide range of differing assumptions and estimation methods. The OLS predictions did not differ drastically from the 2PM or the Tobit, performing similarly on diagnostic measures. Interestingly, despite the 2PM performing better and displaying a lower MAE than did both OLS and Tobit for the EQ-5D prediction, we found a greater MAE when estimating the QALE. This is explained by the fact that the 2PM predicts the EQ-5D with a larger error for the youngest age group, which has the largest impact on QALE estimates.

The anticipated difficulties in mapping IMD quintile groups to the NS-SEC category were also surprisingly small. Despite the seemingly crude method of the mapping of mean IMD-specific EQ-5D scores, the resulting QALE estimates were not significantly different than when mean EQ-5D scores were estimated for IMD quintile groups. Multiple imputations of the missing data had a marginal influence, with a mean difference of 0.3 QALYs across the 360 predictions when using imputed and nonimputed scores. Thus, despite tests indicating that the missing completely at random assumption was violated, assuming that missing values were missing at random had little impact on the final results.

Strengths and Limitations

This study used mortality data for the entire population of England and HRQOL data for a large and representative sample of 25,320 individuals. The validity of the results is further substantiated by

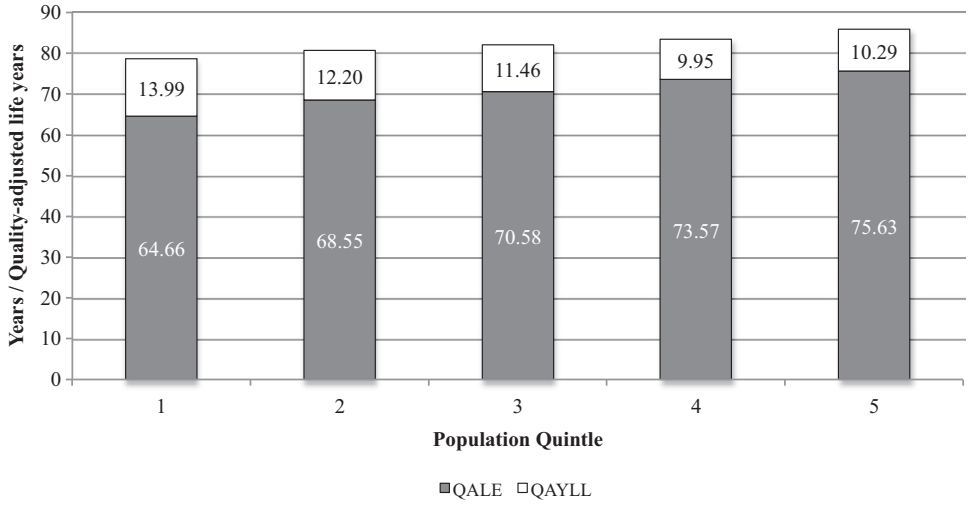

Fig. 1 – Univariate distribution of life expectancy (LE) and quality-adjusted life expectancy (QALE) in England. *Note.* **The total height of each bar is the LE estimate, which can be divided into QALE and quality-adjusted years of life lost (QAYLL) because of morbidity over an individual's lifetime.**

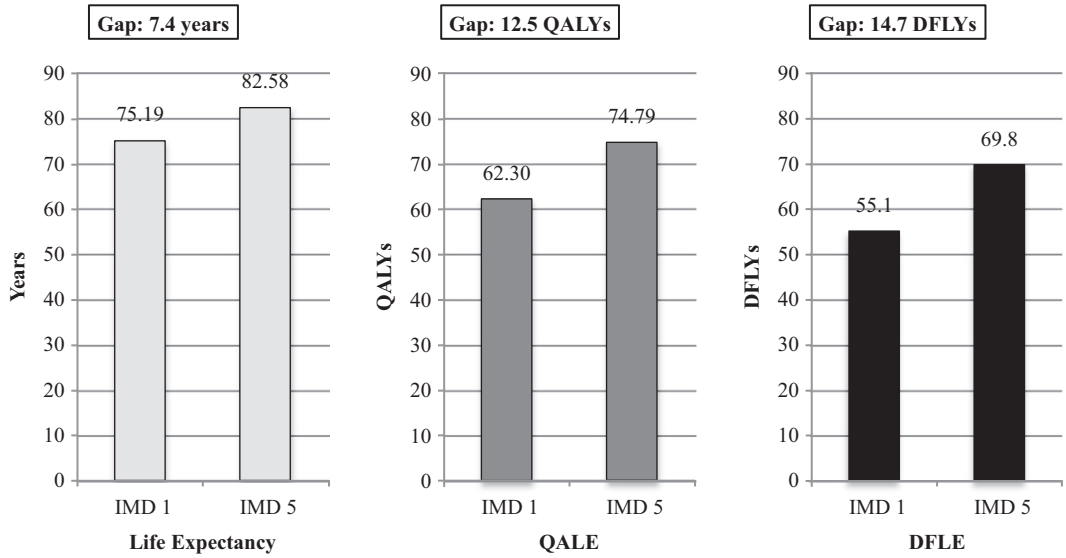

Fig. 2 – Predictions of life expectancy (LE), quality-adjusted life expectancy (QALE), and disability-free life expectancy (DFLE) for males at birth in the most and the least deprived quintile groups. *Note.* DFLE estimates are for 2007 to 2010 and taken from the ONS [25]. LE and QALE estimates are for 2010 to 2012. IMD 1 is the most deprived group, IMD 5 the least deprived. DFLY, disability-free life-year; IMD, index of multiple deprivation; ONS, Office for National Statistics.

the robustness of the findings to alternative SES variables, regression estimators, and ways of handling missing data.

The limitations of the analysis are largely over the estimates of HRQOL. First, mean EQ-5D scores for the groups of interest are likely to be overestimates because the HSE is representative of only the noninstitutionalized population. Those who reside in institutions such as nursing homes or prisons are, on average, likely to be unhealthier than the HSE sample. Because they are also likely to be in lower deprivation groups, this implies that our estimates of inequality are likely to be conservative underestimates.

Second, the subjective nature of the EQ-5D reporting must be acknowledged. As Minet Kinge and Morris [28] note on p. 1869, there may be a systematic reporting bias associated with an individual's SES. For example, those in higher SES groups who are in more sedentary work may have their usual activities inhibited less by illness or injury, resulting in a higher utility score. Conversely, people in low SES groups may have relatively low health expectations and so self-report feeling in relatively good health in particular dimensions, resulting in a higher utility score than do people in high SES groups while experiencing the same level of health from an external clinical perspective. This again will have the effect of underestimating the true degree of health inequality related to the SES.

Third, the assumption that those younger than 16 years have HRQOL equal to that of those in the 16- to 19-year-old age group is unavoidable but improbable. This is verified by the fact that in the HSE sample, 95% of those younger than 16 years reported "Very Good" or "Good" health, compared with only 90% in the 16- to 19-year-old age group, suggesting that our assumption may lead us to underestimate HRQOL for the former, thereby again providing a conservative underestimate of inequality.

Implications and Conclusions

This study is the first to estimate the social distribution of QALE in England. Compared with previous estimates based on simple binary measures of morbidity, our estimates, based on more detailed data on HRQOL, provide more accurate and credible estimates to inform policymakers about the overall extent of health inequalities. The Marmot Review [29] and the Department of Health's Public Health Outcomes Framework [30], which use DFLE and HLE as indicators, respectively, are two examples of prominent public initiatives using crude binary indicators of morbidity.

Our results are also of interest in health technology assessment. First, individual predictions of QALE in Table 4 can be used as reference values for use in decision models. Second, the use of the QALE population distribution is an important empirical step in monitoring the distributional impact of health interventions [9,31]. Although future work could develop our model to introduce additional variables, such as ethnicity, into the analysis, this study brings us a step closer to explicit analysis of the equity-efficiency trade-offs involved in health care resource allocation.

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Supplemental Materials

Supplemental material accompanying this article can be found in the online version as a hyperlink at http://dx.doi.org/10.1016/j.jval.2015.03.1784 or, if a hard copy of article, at www.valueinhealthjournal.com/issues (select volume, issue, and article).

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